

# Investigating Human Priors for Playing Video Games

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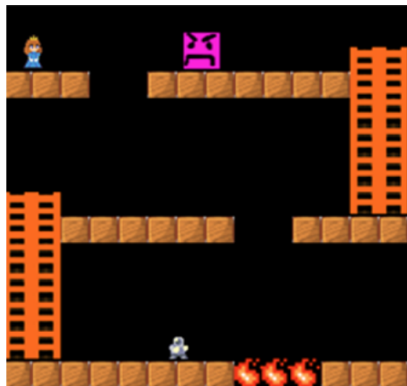
<https://qdata.github.io/deep2Read>

# Motivation

- Humans better than computers at games because they have prior knowledge about the world
- RL requires large amounts of training data in terms of interaction with the environment
- inefficient compared to human players
- A lot of work focusses on improving sample efficiency
- This paper: Quantify role of human priors in games

# Overview: Human Priors in Games

- Removing prior : Humans show difference in performance
- RL Algorithms : same performance
- RL doesn't carry any prior information about the games
- Hence, humans use prior knowledge to solve most tasks
- Ablation study on a game environment to mask different types of priors
- SPecific priors as well as general priors



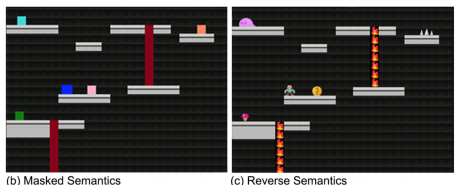
(a) Original Game

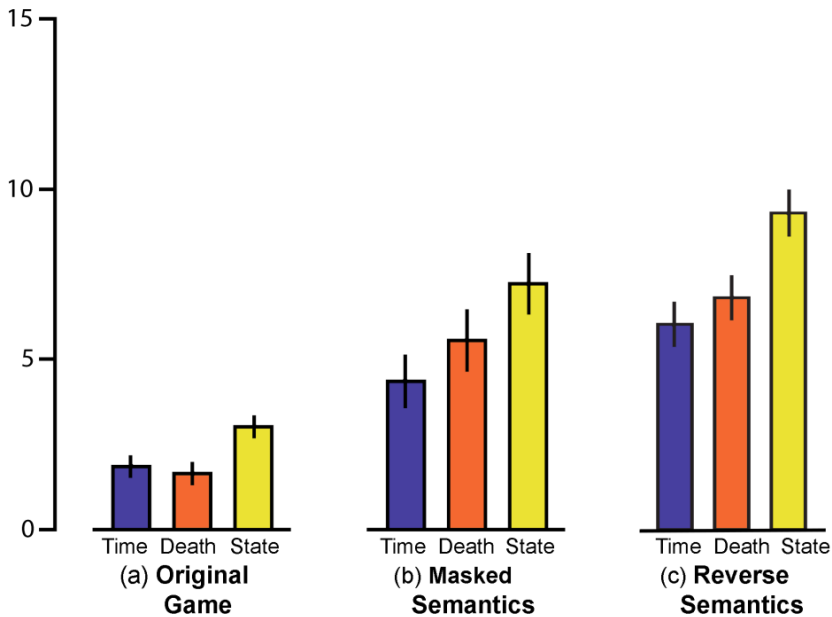
- End goal and reward remains the same
- different versions of the video game with the same underlying structure and reward

- Mechanical Turk
- no information about final goal or reward structure
- Evals:
  - total time taken to finish the game
  - total number of deaths
  - $(x, y)$  position : states

# Prior: Object Semantics

- rendered objects and ladders with blocks of uniform color
- Switch Connotations: Replace slime and spikes with ice cream etc
- enables humans to infer the latent reward structure of the game





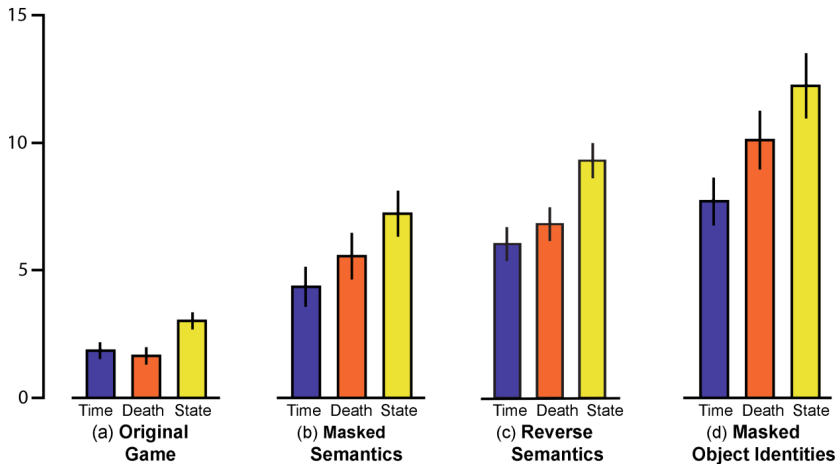
# Human Prior: Objects as sub-goals for exploration

- they are distinct from the background and seem to attract human attention
- cover each space on the platform with a block of different color to hide where the objects are



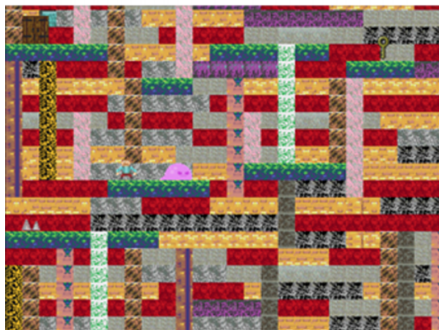
(d) Masked identity of objects



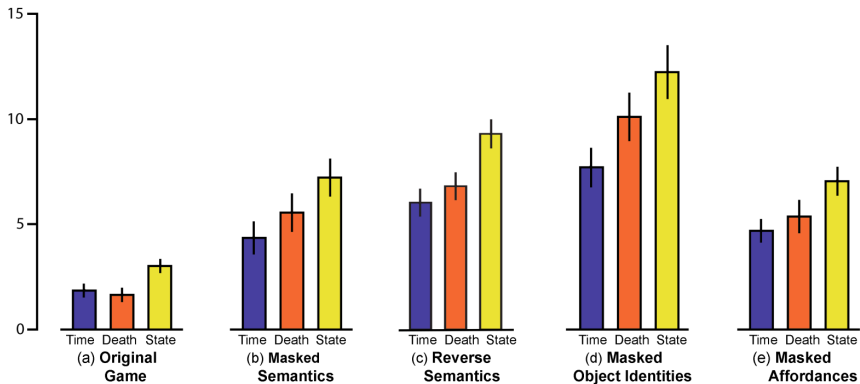


# General Prior: Affordances

- ladders are for climbing, can stand on platforms
- platforms and ladders afford the actions of walking and climbing
- One way to mask affordances is to fill free space with random textures, which are visually similar to textures used for rendering ladders and platforms
- objects and their semantics are clearly observable.

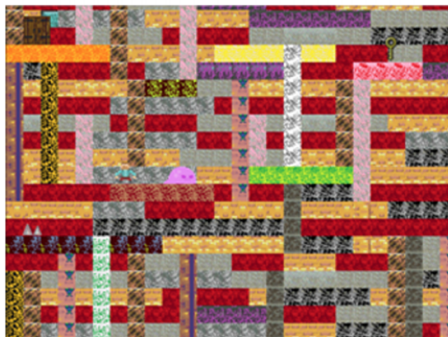


(e) Masked Affordances

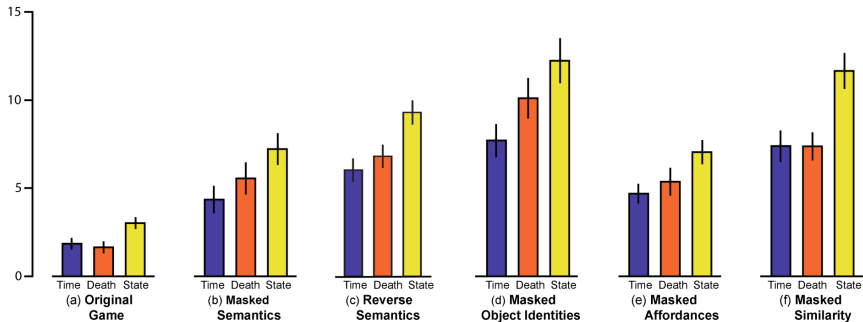


# General Prior: Things that look similar, behave similarly

- once the player realizes that it is possible to stand on a particular texture and climb a specific texture, it is easy to use color/texture similarity to identify other platforms and ladders
- none of the platforms and ladders had the same visual texture

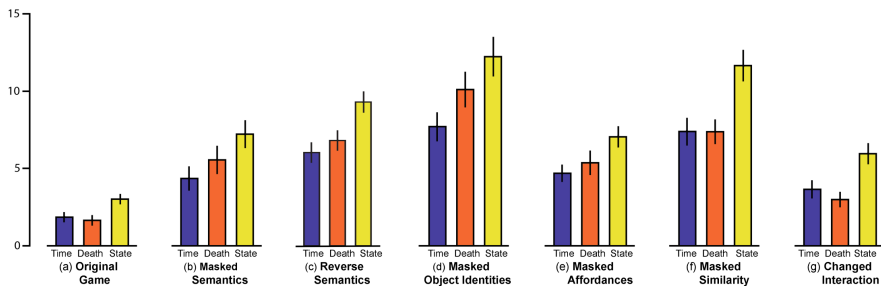


(f) Masked Visual Similarity



# Human Prior: How to interact with objects

- Knowing only what the object is
- Next, How to interact with the object
- jump over a monster, climb a ladder
- zigzag ladders



# Ablation Study

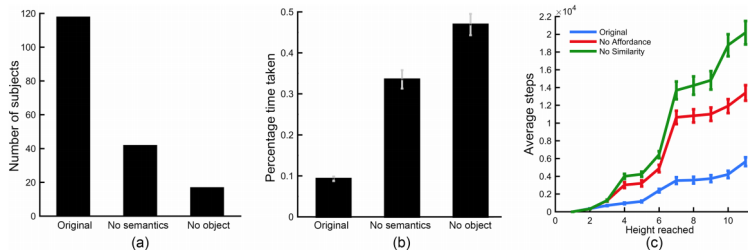


Figure: Average number of steps taken by participants to reach various vertical levels in original version, game without affordance, and game without similarity

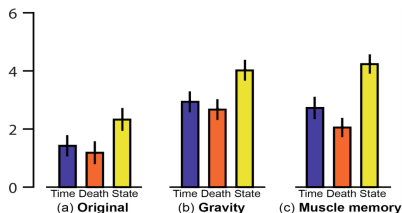


# Human Prior: Physics and Motor Control Priors

- Priors about gravity : objects fall down
- Mask: rotate by 90 degrees

# Human Prior: Physics and Motor Control Priors

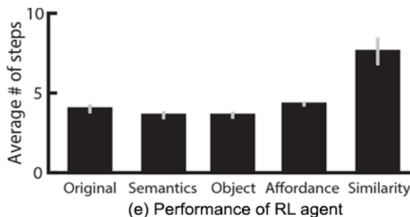
- Priors about gravity : objects fall down
- Mask: rotate by 90 degrees
- Priors about muscle memory: left key makes player go left
- reversed the arrow key controls



**Figure:** Performance of RL agent on various game manipulations. The RL agent performs similarly on all games except for the one without visual similarity

# Comparing RL Agents: Controlling for change in complexity

- It is possible that humans take longer to solve the game because it is visually more complex
- But if RL Agents perform similarly with and without prior that means the modified games are not harder because of visual complexity.
- RL Agents show similar performance
- except : visual similarity
- "due to to the use of convolutional neural networks that implicitly impose the prior of visual similarity rather than simply due to the change in visual complexity."



# Wrong Prior

- rewards in hidden locations
- human participants immediately assume that princess is the goal and do not explore the free space containing hidden rewards.
- a random agent ends up obtaining almost four times more reward than human players
- under-constrained exploration



Figure: Prior information constrains human exploration.

# Possible Solutions

- Goal: Algorithms that require fewer interactions with the environment: sample efficient
- incorporate prior initially instead of learning from scratch.
- learn priors through continual learning